



Evaluation of factors influencing Asian continent ocean health status using a semi-parametric production function



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1. Introduction

The ocean plays a vital role in human survival from the air we breathe to daily weather and climate patterns. The ocean provides a broad range of benefits, from food products to recreational opportunities that improve the livelihoods of coastal communities (Halpern et al., 2012). Healthy oceans are important for food security, jobs and economic development. In 2013, ocean fisheries produced roughly 162 million metric tons of fish and generated over US\$129 billion in exports while securing access to nutrition for billions of people and accounting for 16 percent of total global animal protein (FAO, 2014). Coastal areas within 100 km of the ocean account for an estimated 61 percent of the world's total Gross National Product (GNP) and are of particular importance for developing countries (World Bank, 2017). Overall, healthy oceans, coasts and freshwater ecosystems are crucial for food production and economic growth. On the other hand, an unhealthy ocean can have negative consequences on human health through consumption of contaminated seafood, swimming in polluted water, and exposure to toxins from harmful algal blooms (Knap et al., 2002; Dewailly et al., 2002; National Research Council, 1999; Pew Oceans Commission, 2003; Stegeman et al., 2002; Tyson, 2012; Fleming et al., 2006; Fleming and Laws, 2006).

A healthy ocean is also fundamental to the global effort to mitigate climate change and its impacts. More than 50% of the oxygen we breathe comes from the ocean and more than 3 billion people rely on fish for protein (Thompson, 2017). However, many scientists feel that the ocean health is in jeopardy and needs urgent attention (Halpern et al., 2012; Rojas-Rocha, 2014). Since the 1950s, scientists have measured a steady decline of oxygen in open waters of the North Pacific Ocean on the order of about 0.3% per year. The geological record also demonstrates that low oxygen levels in the ocean can have devastating impacts on marine life (Thompson, 2017). Human activity is continuing to cause rising levels of carbon dioxide in the atmosphere. As these levels rise, so too does the ocean's temperature and acidity. If this trend continues, the consequences for calcium-based marine life, such as fish and shellfish, will be dire, as it will for the ocean's ecosystem in the world, especially on ocean dependent countries on the Asian

continent.

The FAO reported last year that nearly one third of all fish stocks are now at below sustainable levels (FAO, 2014). Coastal communities are apprehensive that the ocean waters are becoming more polluted; the fish caught are smaller now than ever before and that the amount of debris presently found in the oceans is increasing at an alarming rate. The ocean health is deteriorating and has just received an average score of 67 which is a "D" grade (Gewin, 2012). What then is a healthy ocean? An acceptable definition of a healthy ocean can be construed as one that has abundant unpolluted waters and delivers benefits to future generations (Rapport et al., 1998; Samhoury et al., 2012). The definition for ocean health is based on the intrinsic functional benefits that the ocean provides a community (Samhoury et al., 2012; McLeod and Leslie, 2009). The Asian continent one of the largest dependent areas on the ocean for its survival receives a number of benefits from the ocean, and therefore, ocean health is of particular importance to most Asian coastal communities (Whisnant and Reyes, 2015). This study develops a production function of ocean health for the Asian continent to evaluate the factors that influence ocean health. The function measures the elasticities using semi-parametric regression which generates quantitative results that is of interest to scientists and policy makers in determining how manipulation of the variable goals will influence ocean health.

Asia is the largest world continent, accounts for 30 % of the earth's land area, and harbors 60 percent of its population. The occupants are more heavily dependent on the ocean for food, jobs, revenue and recreation than any other people on earth (Dyck and Sumaila, 2010). More than 3 billion people in the region rely on marine coastal resources for their livelihoods and animal protein. However, more than 55% of Asian households depend on income supported by the fisheries sector. The indirect and induced impacts of fisheries production from China and Japan alone account for 60% of economic activity in Asia and 35% globally (Dyck and Sumaila, 2010; FAO Fisheries). In 2008, Asia's marine fishing areas produced 50 percent of the global capture fisheries. Six of the top 10 world producers of fish, China, Indonesia, Japan, India, Philippines and Myanmar are in Asia. The Asian continent accounted for two-thirds of all ocean fisheries available for consumption (FAO Fisheries). For many Asian poor, fish is the major source of

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animal protein. However, while there is an abundance of fish in some of the oceans waters within the exclusive economic zones (EEZ) of countries surrounding the Southern Asian sub-continent, there is little output from wild caught fish in the EEZ of other countries, especially those in the Western Asian sub-region (Whisnant and Reyes, 2015). Given the global economic impact of Asian ocean fisheries, the degree of fisheries exploitation and the imbalance in spatial production, it is important to evaluate the ocean health status of the Asian continent.

The oceans surrounding the Asian continent are unhealthy; that is the oceans' contribution to global poverty alleviation, the provision of food and other economic goods to coastal communities are less than expected. Hence the countries surrounding the Asian oceans receive an average score of 61.32 which is a failing grade and less than the overall global OHI average of 67. This is due to human actions that negatively influence the oceans' ability to provide ecosystem services (Whisnant and Reyes, 2015). Ocean ecosystems are changing rapidly due largely to anthropogenic activities resulting from the inability of institutions to direct human behavior, and actions to manage the oceans to provide human physical, economic and social needs. The ocean health is affected by overfishing, pollution, acidification, climate change, transportation and raw material extraction (Tournadre, 2014). The oceans adjoining the Asian continent are the busiest in terms of shipping traffic in the world. Shipping traffic analysis shows a global fourfold growth between 1992 and 2012, the largest increase in shipping transport being observed in the Indian Ocean and the Chinese seas reflecting the world trade change (Tournadre, 2014). Besides there is a large amount of minerals and natural resources exploited from the Indian and Pacific oceans. The imprudent use of the oceans is bound to affect ocean and human health (Tournadre, 2014). As Liu (2008) stated the health and sustainability of oceans and coastal areas are essential for maintaining global food security and human nutrition. Conservation of the ocean resources contributes to proper eradication of poverty and improves food security.

The ocean health is important to the survival and economic growth of Asian countries (Whisnant and Reyes, 2015), and therefore, the measurement of ocean health and the factors that influence it should send signals to policy makers on the health status of the oceans surrounding the continent. To gauge how well the oceans are doing, a large team of researchers created a wide-ranging measure of the oceans' health. The group consisting of 65 scientists created an Ocean Health Index (OHI) comprising of ten diverse public goals that can be employed to evaluate the impact of changes in fish stocks, extinction risks, coastal jobs, water quality, and habitat restoration (Halpern et al., 2012; Main, 2013). The index measures the defensible delivery of the selected goals now and in the future (Halpern et al., 2008). The index is an assessment tool that scientifically measures key elements from physical, economic and social dimensions of the ocean's health (Halpern et al., 2012). It uses a systematic approach that evaluates the overall condition of marine ecosystems that treat people as integral parts of a healthy system (Halpern et al., 2013). The measure is thought of as constant, computable, translucent and accessible (Samhouri et al., 2012). However, the effects of the endogenous variables and social and environmental exogenous factors on the index should be evaluated to determine its robustness and expediency. In this paper, a health production function for the Asian continent is developed to examine how these goals of ocean health and other socioeconomic variables influence the OHI. The determination of the factors plus exogenous social and environmental variables influencing ocean health adds a new dimension to the body of literature on human and community health. The measurement of the importance of the factors provides a guide to policy makers on their decision to put in place policies to improve ocean health. A conceptual framework is proposed by specifying an ocean health production function with an implicit model; a semi-parametric regression function; an outline of the methods follows; then the presentation of the results and finally the discussion and conclusion.

1.1. Conceptual framework

A healthy ocean provides a broad range of physical, financial and social benefits to coastal communities (Halpern et al., 2012; FAO Fisheries). The problem is how to measure the health status of the ocean? A framework was recently developed to do just that, and was applied to every coastal country in the world (FAO Fisheries). The tool constructed by scientists to assess and monitor the overall health of oceans and coastal ecosystems, as well as the status of components of the system is the ocean health index (Halpern et al., 2012). The novelty of the Index is that it provides an integrated framework to quantitatively assess and compare the condition of the benefits, thus providing a portfolio perspective useful for informing management decisions (Elfes et al., 2014). The Index can also be used to track progress in achieving specific management goals, because it establishes a target or reference point to which current status and likely future conditions are compared (Samhouri et al., 2012).

Ocean health can provide positive as well as negative benefits to humans and communities. OHI, however, uses the benefits as indicators of the health status of oceans. The index also combines key services provided by the ocean (food provision and natural products), extractive services (carbon storage, coastal protection), and cultural (tourism and recreation, sense of place, and values from clean waters and biodiversity), along with central aspects of human well-being that flow from multiple services (artisanal fishing opportunities and coastal livelihoods and economies) (Lowndes et al., 2014). To measure the net benefits of a healthy ocean it is important to develop robust quantitative models to evaluate the effects of physical, economic and social variables on the OHI.

If we measure the services that the ocean provides then the production of health benefits can be represented by a production function in which inputs are combined to produce outputs. A calculated production function of ocean benefits may produce much needed information for policy studies. Grossman (1972) demand function for health care services study sets the stage for economic health care outcome analysis. Early studies on health outcomes from societal inputs examined the social, physical, and environmental determinants (Auster et al., 1969; Hadley, 1982). A recent study by Bayati et al. (2013) using a health production function indicated that the improvement of the health status of Eastern Mediterranean countries requires a focus on the external factors that affect the healthcare system. Many environmental factors that are outside the system affect ocean health and these interact with the internal factors that influence ocean health. In this paper, an ocean health production function based on a-priori human and community, health production functions are employed to evaluate policy decisions. The objective is to use semi-parametric production function and measurable indicators to evaluate the influence of these indicator variables on Asian ocean health.

Semi-parametric regression is a form of regression analysis in which a part of the predictors do not take predetermined forms and the other part takes known forms with the response. Semi-parametric regression, by imposing no a-priori functional form restriction other than continuity, offers an unbiased approach to the estimation of the functional relationship between the dependent and independent variables (Czekaj and Henningsen, 2011; Dougherty, 2007). This functional relationship may be functions with a specified parametric form or may be specified non-parametrically, or semi-parametrically, simply as 'smooth functions', to be estimated by non-parametric means. Under this approach, no mathematical model is assumed for the data distribution (the non-parametric part). The model considered here can be expressed as:

$$Y = X^T\beta + \sum_{j=1}^K f_j(Z_j) + \varepsilon, \quad (1)$$

where $X = (X_1, X_2, \dots, X_d)^T$ is the subset of covariates assumed to be linearly associated with the response, and $Z = (Z_1, Z_2, \dots, Z_K)^T$ is the

subset of covariates used as non-parametric components, $f_1, f_2, \dots, f_K$ are unknown smooth functions, $\beta = (\beta_1, \beta_2, \dots, \beta_d)$ is the vector of unknown parameters, and the model error ε has the conditional mean zero and finite variance σ^2 given (X, Z) . The response variable Y is assumed to be normally distributed with mean μ and variance σ^2 . Thus, to ensure identifiability of the nonparametric functions, we assume that the $f_j(Z_j)$ have mean zero for $j = 1, 2, \dots, K$. Here X^T represents the transpose of the vector X . Because both β and f_j are unknown, this type of model is specified as semi-parametric regression model.

Although significantly improving the utility of linear regression, the semi-parametric model still has limited applications. Semi-parametric models are also quite sensitive to outlying observations, so the generated estimates are unreliable when study data include outliers (Hollander and Wolfe, 1999; Clark, 2013). In this situation, some researchers trim the extreme values prior to conducting the analysis, but the ad-hoc rules used for data trimming are based on subjective criteria so different methods of adjustment can yield different results (Hadley, 1982).

2. Method

The OHI is expressed as a function of a set of ten generally accepted public goals for the contribution they make to society, plus the Human Development Index (HDI) which is a composite measure of average achievement of human development-life expectancy, education and per capita income, GNI that represents the standard of living measured by per capita income expressed in constant 2011 international dollars, Life expectancy and the level of education of a country. Methods for calculating the OHI, and the conceptual framework and rationale for how it is constructed, are detailed extensively by Halpern et al. (2012). The index considers the relations between coastal human societies and ocean ecosystems and their services. The OHI is expressed as a function of a set of ten generally accepted public goals for the contribution they make to society, plus the Human Development Index (HDI), GNI, Life expectancy, the level of education of a country, Marine Protected Areas (MPA), CO₂ emission and other water pollutants (Appendix Table 1). The index considers the relations between coastal human societies and ocean ecosystems and their services. The OHI model is, therefore, represented as:

$$Y_i = f_3(X_3) + f_4(X_4) + f_5(X_5) + f_6(X_6) + f_7(X_7) + f_8(X_8) + f_9(X_9) + f_{10}(X_{10}) + f_{11}(X_{11}) + f_{12}(X_{12}) + f_{13}(X_{13}) + f_{14}(X_{14}) + f_{15}(X_{15}) + f_{16}(X_{16}) + f_{17}(X_{17}) + f_{18}(X_{18}) + f_{19}(X_{19}) + \quad (2)$$

The definition of variables and their anticipated signs are in Appendix Table 1. In the above equation (3), some of the $f_j(X_j)$ will have a linear form (parametric part) and some kept as a smooth function (nonparametric part) depending on the relationship of each covariate associated to each function with the response. The choice of the type of smoother for the nonparametric part depends completely on the practitioner. There are various smooth classes available for different modeling tasks for the user that can be employed. For our analysis we will utilize the commonly used cubic spline as choice of our smoother for the nonparametric part. What defines smooth class is the basis used to represent the smooth function. For cubic splines, basis splines are used. Clark (2013) showed that the use of different smoothers provides non-significant difference in the models and suggest clear indications about some specific variables in the model based on the data.

For our study, cubic smoothing splines are used to estimate the function f_j through the GAM (Generalized Additive Models) function available in the statistical R package mgcv. Smoother is often known as a tool for summarizing the trend of a dependent variable as a function of one or more independent variables say $X_1, \dots, X_p$ (Liu, 2008). Cubic smoothing splines are represented in a GAM model by “ $s(\cdot)$ ”. Note that each smooth function has its own model matrix made up of the bases. So for each smooth covariate we obtain a spline approximation of f_j as:

$$f_j(Z_j) = b(Z_j)\gamma_j, \quad (3)$$

where $b(Z_j)$ is the spline basis function of degree say three for the j^{th} covariate Z_j , and γ_j is the coefficient associated to the basis function $b(Z_j)$. Given a matrix of coefficients S' , we can more formally note a penalized likelihood function:

$$l_p = l(\beta) - \frac{1}{2} \sum_{j=1}^K \lambda_j \beta^T S_j \beta. \quad (4)$$

where, $l(\beta)$ is the usual GLM (Generalized Linear Models), likelihood function and λ_j is the smoothing parameter. The part of the function including λ penalizes the curvature in the function, where λ establishes a trade-off between the goodness of fit and the smoothness, and such an approach allows for less over fitting. That is $\lambda \rightarrow \infty$ results in a straight-line estimate for f_j , while $\lambda = 0$ allows any f that interpolates the data. Thus modeling using equation (1) is equivalent to find for each covariate, a value of β_j and γ_j by minimizing the above penalized likelihood function given in equation (4). The generalized additive model function does just that. In fact, the GAM estimation proceeds by sequentially and iteratively estimating the parametric part by least squares regression and the non-parametric part by non-parametric regression in a flexible manner. As a result, they are widely used in the statistical community with a wide application in environmental health and economics.

We employ the Generalized Additive Model (GAM) estimation technique with mgcv software package to conduct the analysis. The mgcv is an R package for estimating penalized Generalized Linear Models including Generalized Additive Models and Generalized Additive Mixed Models. We examined the assumptions of the GAM model by checking if our response variable OHI is normally distributed.

2.1. Scatterplot matrix

OHI as shown in the scatterplot in Fig. 1 and $f(\cdot) \equiv s(\cdot)$ represents the cubic splines used to estimate the non-parametric part of the model. The dependent variable OHI is the average of 10 of the variables in the model; for the sake of model specification and to avoid singularity some potential contributing variables GNI, HDI, MPA and CO₂ were added to the model. The scatterplot matrix shown in Fig. 1 was obtained by letting the data speak for themselves. That is the association between predictors obtained using cubic spline, and the response was considered linear if the best fit for the association seemed linear and nonlinear if the best fit seemed nonlinear. The scatterplot matrix in Fig. 1 shows us that there is a positive linear association between the score index variables and the variables Wild Caught Fisheries, Artisanal Fishing Opportunities, Natural Products, Lasting Special Places and Mariculture, Habitat, and HDI and could be determined using parametric functions while Carbon Storage, GINI Indices and Species seemed to be curvilinear and can be determined using non-parametric functions.

Hence the best fit for the data may be a model in which some nonlinear approaches are used for variables with a nonlinear expectation that is a linear section or parametric function for those variables with a linear association. It was shown by Clark (2013) that the use of different smoother will provide non-significant difference in the models, but will rather give a clear story about some specific variables to better understand the process behind the data. The choice of the type of smoother for the non-parametric part depends completely on the practitioner.

2.2. Data source and analytical procedure

The Ocean Health Index and ten measured goals of 36 Asian countries for 2013 were extracted from the ocean health EXCEL spread sheet of 2014. The OHI was first published in 2012 and modified in 2013. The changes did not result in any major shifts in the overall

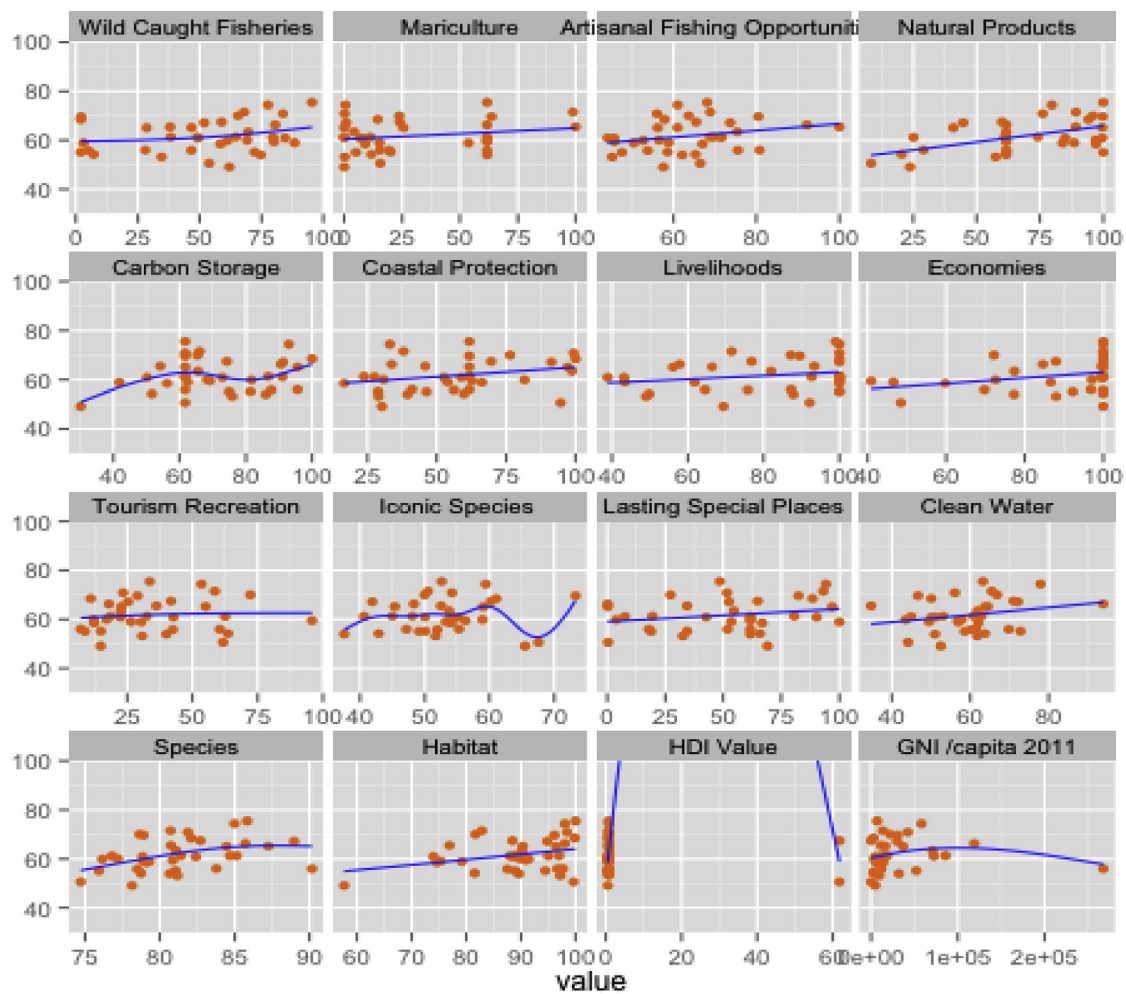


Fig. 1. Scatterplot matrix for ocean health.

Table 1

Descriptive statistics for Asian ocean health goals and socio-economic variables.

Variables	n	mean	sd	median	trimmed	mad	min	max
Index Score(X_2)	36	61.72	6.60	61.04	61.59	7.63	49.09	75.45
Wild Caught Fish(X_4)	36	52.25	27.59	58.64	53.55	29.04	1.98	95.47
Mariculture(X_5)	36	15.20	25.28	6.06	9.49	8.99	0.00	100
Artisanal Fishing(X_6)	36	63.77	12.73	62.86	62.92	10.16	44.16	100
Natural Products(X_7)	36	53.34	40.28	60.62	54.01	54.01	0.00	100
Carbon Storage(X_8)	36	57.22	34.74	67.17	58.95	29.68	0.00	100
Coastal Protection(X_9)	36	46.73	31.81	43.40	46.15	28.84	0.00	100
Livelihoods(X_{11})	36	81.55	20.37	88.71	83.68	16.74	38.87	100
Economics(X_{12})	36	88.81	17.22	99.81	92.04	0.27	40.88	100
Tourism, Recreation(X_{13})	36	32.83	21.13	27.66	31.14	18.97	0.00	95.84
Iconic Species(X_{15})	36	52.92	7.39	52.98	52.62	5.32	37.57	73.32
Special Places(X_{16})	36	42.93	34.27	45.58	41.80	46.48	0.00	100
Clean Water(X_{17})	36	59.27	11.10	60.50	58.89	10.21	34.74	93.92
Biodiversity(X_{18})	36	84.68	6.82	85.62	85.45	6.57	61.72	93.41
Species(X_{19})	36	81.31	3.66	80.95	81.14	3.38	74.71	90.17
Habitat(X_{20})	36	89.33	9.36	90.24	90.33	9.70	57.69	100
HDI Value (index) (X_{23})	36	0.73	0.11	0.75	0.74	0.14	0.50	0.90

scores from 2012 to 2013. Scores were measured in 2014, 2015 and 2016 but the changes did not result in any major differences. We used 2013 to obtain the maximum number of OHI observations that corresponded to the observations of the other data sources of the HDI, GNI and environmental data. HDI and GNI data were taken from the United Nations Development Program (2013) and the environment data were extracted from the World Bank (2015) Environment Bank database. The term “Asia” is a cultural concept, whereas the sub-region is described as

the distinct geopolitical identities of the continent. These classifications are Western Asia, Central Asia, Southern Asia, Eastern Asia, and Southeastern Asia. For this paper we adhere to the geopolitical classification (Halpern et al., 2015). The countries included in the study are seen in Appendix 1, table 2.

The OHI consists of extractive goals (food provision, natural products and artisanal fishing opportunities), supporting goals (coastal protection and carbon storage), cultural goals (tourism and recreation

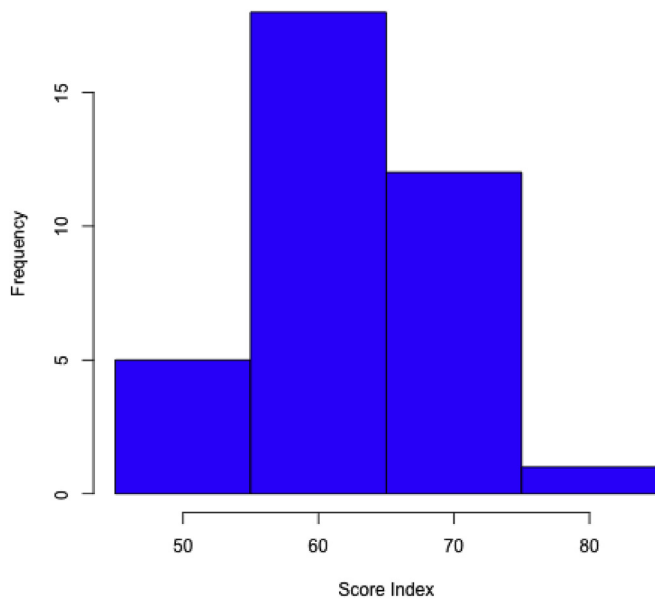


Fig. 2. Frequency distribution of Asian Countries Ocean Health Index.

and sense of place), economic goals (livelihoods and economies) and conservation goals (clean water and biodiversity). Each goal is assessed by its current status relative to an established reference value intended to represent a societal objective and its likely future (Halpern et al., 2015). The OHI recognizes linkages between human societies and ocean ecosystems and that people are part of coastal and ocean systems within the countries EEZ. Data from the Human Development Index were taken from the United Nations Development Program (United Nations Development Programme, 2013).

3. Results

There were 36 countries in the sample with 41.7 percent of them from Western Asia. The OHI had an average score of 61.72 with a minimum of 49.09 and a maximum of 75.45 (Table 1) and most of them were in the range of 55–65 (Fig. 2). The sub-goal Habitat had a mean score of 89.33, while species had 81.83. Economies had a score of 88.11 and Livelihoods had an average score of 81.55. Wild caught fish had an average of 52.25 with a minimum of 1.98 and a maximum of 95.47. The South Eastern Asian sub-region had a mean OHI of 60.6 with East Timor having the minimum score of 46.49 and Thailand the highest of 71.49 while the Eastern Asia had an average of 64.05 with Taiwan having the minimum score of 56.02 and China the maximum of 69.61. The south Asia had a mean of 58.17 with Pakistan having the lowest score of 49.09 and Bangladesh the highest of 68.46. The Western Asia sub-region had a mean of 62.93 with Georgia having the maximum of 75.45 and Bahrain the lowest of 53.96 (Appendix table 2).

3.1. Importance of model influence of predictors

Table 2 presents the relative influence of the predictor variables which determine those from the highest to the lowest partial standardized influence on the dependent variable. The relative influence of predictors is generated by the gradient boosting machines (GBM) algorithm, which is a powerful machine-learning technique that has shown considerable success in a wide range of applications. GBM can effectively capture complex non-linear function dependencies (Hastie, 2007). Influences do not provide any explanations about how the variable actually affects the response. But the resulting influences can be used for both forward and backward selection procedures. The relative influences are further standardized so that they add up to 100%. The relative variable influence shows that Coastal Protection

Table 2
Influence for nonparametric Asian data.

Variables	Relative Influence
Coastal Protection (index) (X_9)	19.2150987
Tourism, Recreation (index) (X_{13})	17.0405767
Caught & Mariculture (index) (X_3)	16.9287072
Natural Products(X_7)	16.0848328
Livelihoods & Economics (index) (X_{10})	8.5295157
Biodiversity (index) (X_{18})	5.7987307
Clean Water (index) (X_{17})	5.0965614
GNI/capita \$ 2011 X27	4.3910605
Sense of Place (index) (X_{14})	2.4429978
Artisanal Fishing Opportunities (index) (X_6)	1.9902503
HDI Value (index) (X_{23})	1.5023718
Carbon Storage (index) (X_8)	0.9792964

contributed 19.21% to the model and in second place is Tourism and Recreation with 17.04%. Wild Caught and Mariculture, and Natural Products contributed 16.92% and 16.08%, respectively. HDI and Carbon Storage contributed the least with 1.50% and 0.98%, respectively.

3.2. Semi-parametric model results

Several models tried with both forward and backward selection procedures, with some variables kept linear (parametric part), were based on their linear future with the response variable OHI. The variables that posed multicollinearity problems were dropped from the equation. Most variables remained linear due to their effective degrees of freedom (*edf*) that suggest that their association with the response variable OHI seemed to be left linear during the fitting process. In fact, an effective degree of freedom equaling to one suggests that the linear fit is better for modeling the given predictors with the response (Clark, 2013). Table 3 shows that the semi-parametric model had a good fit with an adjusted R^2 of 0.99 and a distance variance of 99.7% percent. The GCV (Generalized Cross Validation) was 0.511 that is the quantity providing the best smoothing parameter that minimizes the GCV. Thus the smaller the GCV is the better is the fitting. The scaled deviance estimate (which represents the variance estimate in this case) is 0.236

Table 3
Semi-parametric model for Asian ocean health.

Parametric coefficients:	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	−0.00688	0.002150	−3.203	0.00584**
Food Provision (X_3)	0.10590	0.004153	24.832	2.596e-14***
Artisanal Fishing (X_6)	0.09939	0.011080	8.967	1.129e-07***
Natural Products(X_7)	0.10420	0.003218	32.374	3.84e-16***
Carbon Storage(X_8)	0.00993	0.001098	9.048	9.89e-08***
Coastal(X_9)	0.09857	0.048500	20.324	6.01e-13***
Livelihoods and Economics (X_{10})	0.01150	0.091200	12.612	8.68e-10***
Tourism and Recreation (X_{13})	0.10270	0.050099	20.509	5.22e-13***
Sense of Place(X_{14})	0.10 42	0.060560	17.201	7.99e-12***
Clean Water(X_{17})	0.1033	0.013440	7.688	8.61−07***
Biodiversity(X_{18})	0.1026	0.032390	3.168	0.00589**
HDI Value(X_{23})	0.6186	0.020450	3.025	0.00796**
Marine Protected Area (X_{31})% of territorial waters	−0.01997	0.017320	−1.153	0.26572
Nitrous Oxide Emission	−0.07630	0.014600	−0.666	0.5101
Approximate significance of smooth terms:				
	edf	Ref.df	F	p-value
GNI/capita 2011 s(X_{27})	5.709	3.655	1.72	0.018

R-sq.(adj) = 0.99 Deviance explained = 99.7%.

GCV = 0.5115 Scale est. = 0.23648, n = 36.

Table 4
Elasticities from the semi-parametric model.

Variable	Elasticity for Semi-parametric
Food Provision(X_3)	0.08924
Artisanal Fishing(X_6)	0.10287
Natural Products(X_7)	0.10493
Carbon Storage(X_8)	0.11871
Coastal(X_9)	0.08904
Livelihoods and Economies(X_{10})	0.15931
Tourism and Recreation(X_{13})	0.05434
Sense of Place(X_{14})	0.08038
Clean Water(X_{17})	0.09891
Biodiversity(X_{18})	0.14221
HDI Value(X_{23})	0.07356

and of course the lower it is the better is the fit and it is connected to the adjusted R^2 , and the lower it is the higher the adjusted R^2 . This together with the relatively small GCV confirms that, the semi-parametric model has a good fit.

The elasticities for the parametric part of the semi-parametric model were computed (Table 4). The predictor variable GNI/capita was designated the smooth function based on its relationship with the OHI as seen in Fig. 1. It had a positive effect on OHI. Livelihoods and Economies had the highest elasticity of 0.15 which means that an increase of one percent in Livelihoods and Economies results in a 0.15% increase in OHI. Biodiversity has an elasticity of 0.14 while Carbon Storage, Natural Products and Artisanal Fishing had elasticities of 0.11, 0.10 and 0.10, respectively. Clean water also had a positive effect on OHI. The semi-parametric model performed well and had most variables positive and significant at $\alpha = 0.05$, and HDI had a positive effect on OHI. A one percent increase in HDI has a 0.07 percent improvement in OHI.

4. Discussion

The scatterplot shows that the final model can be represented by a function containing parametric coefficients. The influence factors show that the variable Coastal Protection which measures the degree of protection offered by communities to oceans that people value contributed significantly to explained variance of OHI. In second place are Tourism and Recreation, and Wild Caught and Mariculture in third.

The semi-parametric regression produced a model with good fit as indicated by the adjusted R^2 and the deviance explained. Most variables were significant with the anticipated signs. The influence of two major oceans, Indian and Pacific, on the global Asian Ocean Health and Biodiversity is important. An expansion of Biodiversity should be considered by policy makers as the first effort to improve Ocean Health. Such enhancement includes habitat management, regulation, enforcement and the encouragement of the adoption of practices that foster the proliferation of bio-diverse species. Development of habitat and species sub-goals is essential to the enhancement of OHI through the reduction of habitat devastation which poses the greatest threat to Biodiversity (Ovaskainen, 2012).

The various practices that have been noted to engender Biodiversity improvement include catch shares and quota based systems. Reimer et al. (2015) stated that in both forms of access, fishers have a direct stake in the output of their fishery as well as an incentive to comply with the regulations. The variable MPA was not significant, but expansion of marine protected areas (MPAs) for the preservation of species that are likely to be lost from habitat fragmentation (Ovaskainen, 2012) is a sound strategy to expand biodiversity (Sala et al., 2013; Divakarannair, 2007). A number of countries such as Iraq, North and South Korea, Taiwan and Syria had no established MPAs or there were no recorded data of MPAs (Fig. 3). The first number in bracket next to the country on the map indicates the protected territorial areas in km² and the second figure indicates the percentage of territorial area covered by MPA.

Another goal that affects OHI is Livelihoods and Economies. This variable is of particular importance to the Asian continent economies since a large portion of the Asian population depends on ocean fisheries for their existence. Over 400 million people in the poorest countries in Asia, particular South Asia, obtain at least half of their essential protein and mineral intake from the catch of small-scale fisheries (Saha and Ali, 2006; Dulvy and Allison, 2009; Bell et al., 2000). Added to this, the Pacific route traversing the continent is the busiest in the world in terms of goods transferred on shipping vessels. This means that the ocean makes a serious contribution to the economic livelihood of most of the ocean people. Fish production in Asia is small scale and employs large numbers of people throughout the Asian continent.

Carbon Storage has a major effect on OHI and the improvement in this variable is likely to influence OHI. The ocean represents the largest potential sink for anthropogenic CO₂. It already contains an estimated 40,000 GtC (billion metric tons of carbon) compared with 750GtC in the atmosphere and 2200 GtC in the terrestrial biosphere (Allison, 2011). During the period 1880 to 1990, modeled results suggest that monsoon Asia as a whole released 29.0 Pg C, which represents 50% of the global carbon release for this period. Carbon release varied across three sub-regions: East Asia (4.3 Pg C), South Asia (6.6 Pg C), and South East Asia (18.1 Pg C) (Herzog et al., 2004).

Artisanal Fishing and extraction of Natural Products are important variables influencing Ocean Health. Artisanal Fisheries Opportunities indicate how individuals in a community access fishing opportunities to support their livelihoods. Fish harvesting is usually done by a large number of limited resource fishermen and few larger fishing businesses. There is a belief that the involvement of large numbers of limited resource poor fishers may have serious consequences on their food provision and human well-being, but on the other hand, the extraction of large quantities of fish might undermine progress in biodiversity improvement and may have a deleterious effect on OHI. Artisanal Fisheries will have a positive effect on OHI. A one percent increase in Artisanal Fisheries will have a 0.10 percent increase in OHI.

Clean water also has a major impact on OHI. Clean Water influences OHI and can be controlled by communities at reasonable costs. A one percent improvement in water quality results in a 0.09 percent increase in the OHI index. Unfortunately, water quality in the Pacific and Indian oceans is affected by large quantities of waste dumped in the water. Scientist found large and extensive garbage patches in the Indian and North Pacific oceans. These plastic patches impede water quality and destroys the ocean ecosystem. Asia has the maximum number of polluted rivers more than anywhere else in the world. Most of them contain bacteria from human waste. For example, about 85 percent of the total ground water in Bangladesh has contaminated ground water (Divakarannair, 2007). Polluted beaches that make swimmers sick generate major economic losses to coastal communities. The reduction in non-point source pollution; protecting water from pollution by defending the Clean Water Act and the establishment of pollution limits can help reduce the amount of waste water entering the beach.

Coastal Protection provides defense against flooding and erosion, caused by waves, winds, currents and littoral drift, sea level rising from climate change and the ice cap melting. For coastal protection, it is hypothesized that all coastal areas have value (and equal value) and the total area and condition of key habitats within each EEZ influence OHI. A one percent improvement in Coastal Protection will result in a 0.09 percent increase in OHI. The habitats that provide protection to coastal areas for which global data are available include mangroves, coral reefs, sea grasses, salt marshes, and sea ice (Sala et al., 2013).

It is important for policy makers to note that Livelihoods and Economies and Biodiversity increases may have the greatest effect on OHI and improvement may be within the reach of even the poorest country. The use of catch based management coupled with coastal shoreline protection may have some measure of success on Biodiversity improvement and can be executed without much enforcement or regulation. The Asian economies depend on the oceans for their living and

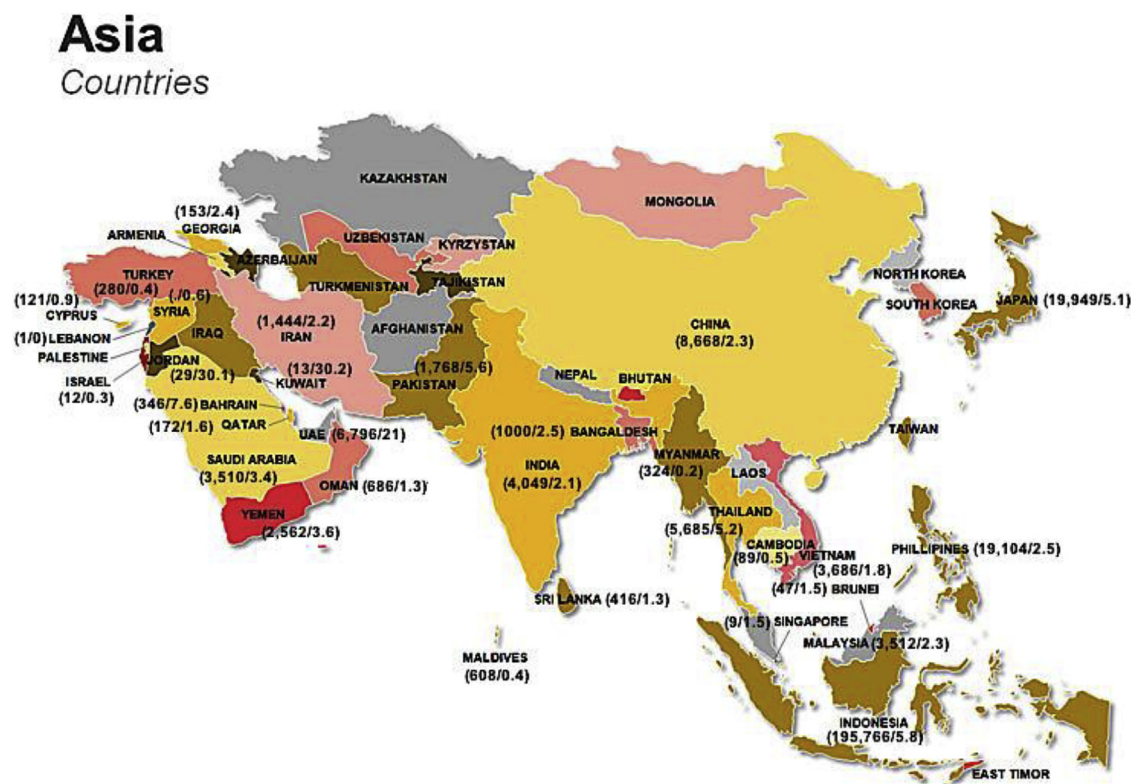


Fig. 3. Asian countries with ocean territorial areas and percentage coastal areas in marine protected areas (First number is area and second is percentage).

any improvement in these areas are appreciated.

5. Conclusion

The study shows that ocean health of the Asian continent varies by regions, the South Eastern Asian sub-region had a mean OHI of 60.6, the Eastern Asia average was 64.05, the south Asia mean was 58.17 and the Western Asia sub-region had a mean of 62.93. The Asian continent which depends greatly on the ocean for its survival has a low and almost failing OHI grade. Livelihoods and Economies and Biodiversity had the largest elasticity which indicates that attempts to manipulate these variables may have the greatest impact on ocean health. The areas for improvement with the largest impact require sacrifice, regulations and law enforcement. Improvement in Livelihoods and Economies is a way of bolstering OHI though the overexploitation of the ocean resources may negatively influence ocean health. Therefore, policy makers of the Asian continent should search for the optimum balance of extraction of ocean benefits to maintain sustainable ocean health. The other goals to which attention should be placed are Carbon Storage, Artisanal Fishing, Natural Products, Clean Water and Coastal Protection. GNI and HDI were significant in the improvement of OHI which means that OHI can be improved through human capital improvement, education income enhancement, or awareness creation using the multimedia system. This study is of particular interest to global policy makers to assist in the manipulation of environmental and socio-economic indicators to improve ocean health. Since Asia is one of the largest users of the ocean for human survival, the study results provide insights of the factors to modify that will have the greatest influence on ocean health. The study can be improved if accounts are taken of the specific policies formulated and emphasized in each country. Unfortunately, the ocean management index which could be used to improve the study is only available for 20 countries and most of the Asian countries are not included on the list.

Acknowledgements

The authors would like to thank NORED for its assistance in preparing this doc.

Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.ocecoaman.2018.03.021>.

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